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# Washington State Public Teachers' Ambient Positional Instability From A Statistical Approach of Retrospective Study & Prospective Study


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# Washington State Public Teachers' Ambient Positional Instability From A Statistical Approach of Retrospective Study & Prospective Study

## Abstract

The purpose of this research is to study the movements of teachers' churn rate in the state of Washington over the past 14 years. The research of teachers' churn rate is an integrative study, with retrospective part and prospective part. Retrospective study includes the analysis of descriptive statistics (level I), statistical inference (level II) and causal inference (level III) (Berk, R.A. (2016) *Statistical Learning from a Regression Perspective*. Philadelphia, PA: Springer). Prospective study is mainly about forecasting and statistical inference that generated from the predictions. In this research, we are using longitudinal data analysis. The good point of longitudinal data analysis is that it provides us with the data in the past fifteen years with keeping track of the status of all K-12 teachers in the State of Washington. A Comprehensive meta-analysis research on teacher career trajectories conducted by Borman and Dowling shows that very a few previous studies used long-term longitudinal data to properly track the movement of teachers (Borman & Dowling, 2008). From statistical respect, longitudinal studies always provide better results than other approaches when time is a factor in the analysis. Our research is the holistic contribution from the whole project panel, especially under the advising of Professor Robert Boruch, who is also the director of the whole research project series. Bowen Cai takes the responsibility of retention & churn rate calculating, statistical modeling (including machine learning algorithms and time series forecasting) and statistical analysis from the respects of survey methods and design.

## Keywords

statistics, education

## Disciplines

Applied Statistics | Education | Longitudinal Data Analysis and Time Series | Science and Mathematics  
Education | Secondary Education and Teaching | Statistical Methodology | Statistical Models | Theory and Algorithms

**Washington State Public Teachers' Ambient Positional Instability**

**From A Statistical Approach of**

**Retrospective Study & Prospective Study**

**2003-2016**

**Bowen Cai, Robert Boruch**

**University of Pennsylvania**

**05/03/2017**

## **Abstract**

The purpose of this research is to study the movements of teachers' churn rate in the state of Washington over the past 14 years. The research of teachers' churn rate is an integrative study, with retrospective part and prospective part. Retrospective study includes the analysis of descriptive statistics (level I), statistical inference (level II) and causal inference (level III) (Berk, R.A. (2016) *Statistical Learning from a Regression Perspective*. Philadelphia, PA: Springer). Prospective study is mainly about forecasting and statistical inference that generated from the predictions. In this research, we are using longitudinal data analysis. The good point of longitudinal data analysis is that it provides us with the data in the past fifteen years with keeping track of the status of all K-12 teachers in the State of Washington. A Comprehensive meta-analysis research on teacher career trajectories conducted by Borman and Dowling shows that very a few previous studies used long-term longitudinal data to properly track the movement of teachers (Borman & Dowling, 2008). From statistical respect, longitudinal studies always provide better results than other approaches when time is a factor in the analysis. Our research is the holistic contribution from the whole project panel, especially under the advising of Professor Robert Boruch, who is also the director of the

whole research project series. Bowen Cai takes the responsibility of retention & churn rate calculating, statistical modeling (including machine learning algorithms and time series forecasting) and statistical analysis from the respects of survey methods and design.

### **Introduction**

High teacher instability, caused by teacher attrition and migration, has potentially seriously compromised the right of students to be educated (Rayes, Oh, Lee, & Boruch, 2016). This issue is attracting more and more attention from scientists and researchers in educational area. Many scholars conducted surveys on this topic. One report related to this topic that I have read was “Teacher Attrition and Mobility”, which was conducted by Rebecca Goldring, Soheyla Taie, and Minsun Riddles in September 2014. It was about Teacher Follow-up Survey (TIF) sponsored by the National Center for Educational Statistics (NCES). TIF survey focused on a nationally representative sample (by using probability sampling methods) of public and private K-12 school, principals, and teachers in the United State of America in the year of 2012-2013 to look into teachers’ attrition and mobility (Goldring, Taie, & Riddles, 2014). Some findings in TIF survey were:

“Of the 3,377,900 public school teachers who were teaching during the 2011-2012 school year, 84 percent remained at the same school, 8 percent moved to a different school, and 8 percent left the profession during the following year” (Goldring et al., 2014).

“Among public school teacher movers, 59 percent moved from one public school to another public school in the same district, 38 percent moved from one public school district to another public school district, and 3 percent moved from a public school to a private school between 2011-2012 and 2012-2013” (Goldring et al., 2014).

“About 8 percent of public school teacher leavers left teaching involuntarily in 2012-2013” (Goldring, et al., (2014)).

As a matter of fact, many reasons can account for teachers' attrition and mobility. Harris and Adams in the article of “Understanding the Level and Causes of Teacher Turnover: A Comparison with Other Professions” pointed out that they found some evidence that the relatively high ratio of pensions-to-salaries in teaching partially explained the behavior of changing positions (Harris, D.N., & Adams, S.J. (2007)). Per my perspective, the local

economy and environment are also some possible factors to influence teachers' attrition.

In order to better analyze the influence of teachers' instability, our research panel put forward a concept of churn rate, which is similar to the turnover rate, defined as:

$$\frac{\text{New Comers in the Subject}_t + \text{Leavers in the Subject}_t}{\text{Number of teachers in the Subject}_{t-1}}$$

Subject in our research refers to STEM subjects.

The least possible value of the churn rate is 0, but there is not upper limit of the churn rate. This paper mainly focuses on discussing the teachers' churn rates within STEM (Science, Technology, Engineering and Mathematics) fields in the state of Washington. In terms of construct, the paper can be divided into four parts: The first part is data trimming and investigation of the teachers' full time employment. The second part is statistical computing of the churn rate and the retention rate. The third part is about forecasting methods of the churn rate. The fourth part is conclusion and discussion. The whole project is developed in the environment of the statistics software R, and selected graphs and code are provided.

### **Data Trimming and Investigation into the Dataset**

The dataset we have is not clean. We need to take some time to trim. Due to the differences of grade level, school level, certificate type and other reasons, many teachers are listed more than once in different rows even they have the same certificate number. There are also some NAs in the dataset. However, those NAs are not missing values. Some teachers are teaching in several endorsements, but some teachers only teach in one endorsement. The difference in the number of endorsements makes this happen. Therefore, we can fill character “UNKNOWN” into the blank cells. Some R functions are good to use here. Unique () function in R can get rid of the redundant rows. There are also some redundant spaces append to the words. We can use “Replace” function in Excel to erase all the redundant spaces and resave the datafile into .csv file and read into R.

FTE, also known as “Full Time Employment”, is another variable that we need to notice. Usually speaking, FTE should be less than 1, if we consider one to be the full time employment. However, we find that some certificate numbers have FTE much larger than one. If we withdraw a sample of 898 teachers, 473 teachers are listed more than once, whose FTEs are larger than 1. The percentage is 52.67%. For example, Certificate number 203128D has FTE summed to be 1.400, and Certificate number 216661R has FTE summed to be 1.988.



The largest Certificate number has FTE summed to be 6.000. Apparently, it cannot happen because no one can work 48 hours per day. There must have something wrong. The summary table can also indicate this.

```
summary(df.summary)
Certificate.      FTE      fte
Length:102      Min.   :0.1540  Min.   :0.154
Class :character 1st Qu.:0.4000  1st Qu.:0.609
Mode  :character Median :0.6670  Median :1.200
                        Mean  :0.6755  Mean   :1.361
                        3rd Qu.:1.0000  3rd Qu.:2.000
                        Max.   :1.0000  Max.   :6.000
```

I look into the dataset, and conclude there are three possible reasons to explain why FTE > 1.0.

First, teachers are teaching in different grades. Each grade gives those teachers a certain value of FTE.

Second, teachers are teaching in different schools. Each school gives those teachers a certain value of FTE.

Third, teachers are having the same certificate number, but different types. FTE may also get counted more than once in terms of the different certificate types.

The way I deal with FTE with values larger than one is to round them down to 1, and

consider those teachers as full time employers. However, it may be biased, because these teachers are part-time workers in several spots. The summation greater than one cannot indicate that they are really full time teachers.

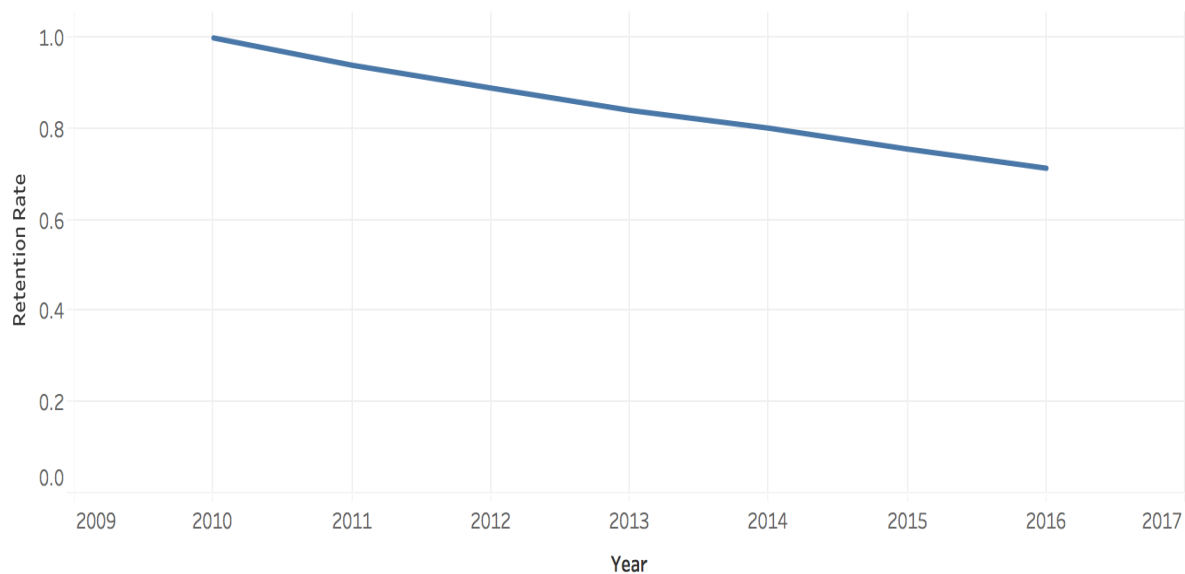
### **Churn Rate Computing**

We have so many useful information such as teachers' name, birthday, endorsement, grade level, school district, school name, certificate number, certificate type, code and so on. Each certificate number is unique to each teacher. Endorsements are considered to be the subjects that the teacher is currently teaching, as suggested by the University of Washington College of Education "Endorsement is specific subject matter listed on teaching certificate that the teacher is qualified to teach in Washington State". One teacher may have more than one endorsement. As a matter of fact, 90 percent or more teachers have more than one endorsement. There are so many ways to define a teacher to be a STEM teacher. The way I choose is that if this teacher is teaching at least one subject within the STEM field, then this teacher is considered to be a STEM teacher. The pool of STEM subjects keeps changing year over year. We need to update the pool every year. Luckily, only new subjects come into the

pool, but no old subjects get removed. After some efforts, I get the churn rates over the period from 2005-2016 are: 2005-2006: 0.161, 2006-2007: 0.333, 2007-2008: 0.167, 2008-2009: 0.181, 2009-2010: 0.144, 2010-2011: 0.119, 2011-2012: 0.120, 2012-2013: 0.139, 2013-2014: 0.141, 2014-2015: 0.137, 2015-2016: 0.136. As we predicted before that the policy interference would account for the churn rate movements in the period of 2007-2009, and the significant spike took place in 2007, which is 33.3%. We also notice that the churn rates fluctuate within a small range from 11.9% to 14.1% after the year 2010 because the public environment is stable.

### **Cohort Retention Rate at the State Level**

The retention rate is defined as the percentage of teachers in the base year that still had an assignment in Washington State in subsequent years, regardless of a change in the grade, subject, or full-time equivalency of the assignment (Rayes et al, 2016). I calculated the retention rates from 2010-2016, which are 2010: 1.000, 2011: 0.940, 2012: 0.890, 2013: 0.841, 2014: 0.802, 2015: 0.756, 2016: 0.714. If we draw the picture, the graph looks like this.



We see that the retention rates follow a straight decreasing trend, with constant decreasing rate of 5% per year. We can expect the retention rate of the year 2017 will be around 0.66. It is not strange that the line is straight, because the churn rates after 2010 are quite stable. In the environment without policy interference or social turbulence, the retention rates should keep constant decreasing rate, which means the loss of teachers is steady. This finding is also compatible with what we got from the paper “Ambient Postional Instability in Minnesota Schools: 2010-2011 to 2014 to 2015 Preliminary Report” at page 26.

### **Cohort Retention Rate at the District level**

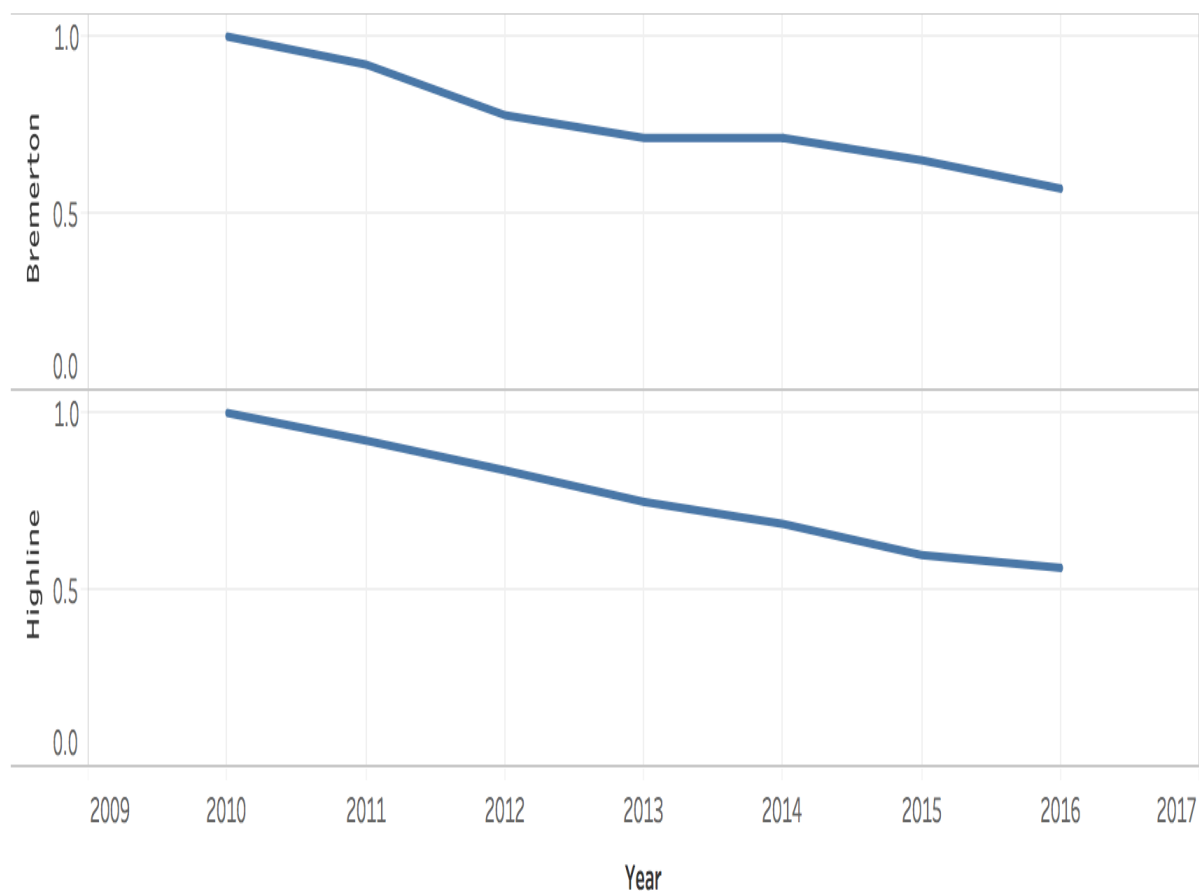
In total, there are 294 school districts in the state of Washington. Some school districts

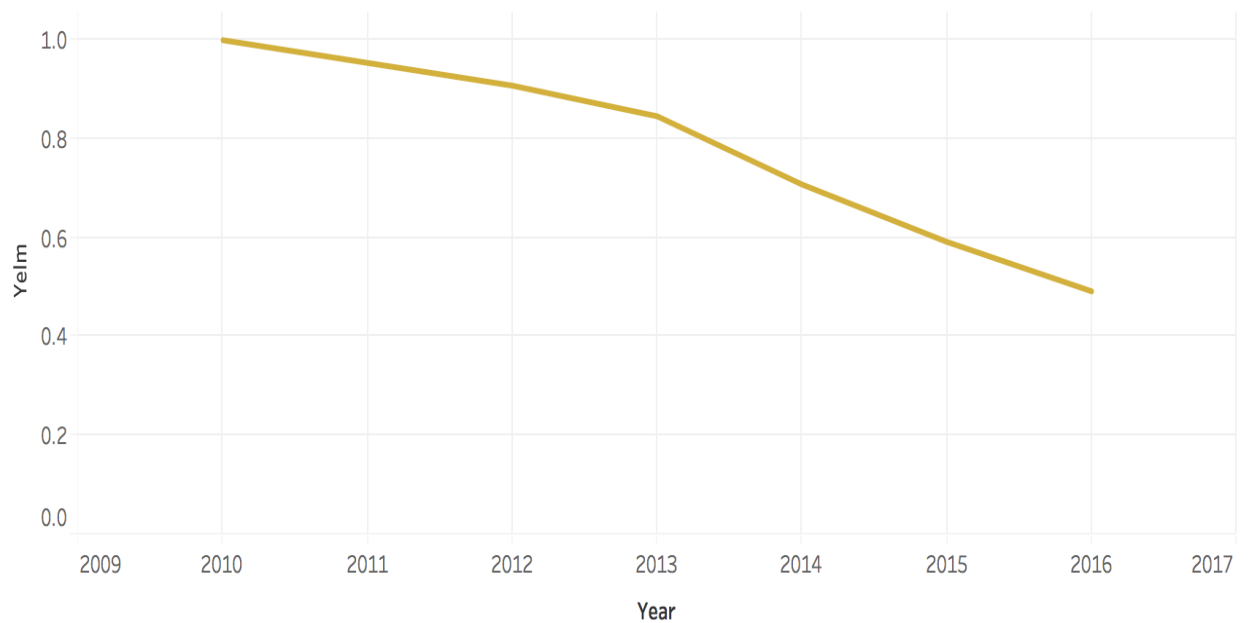
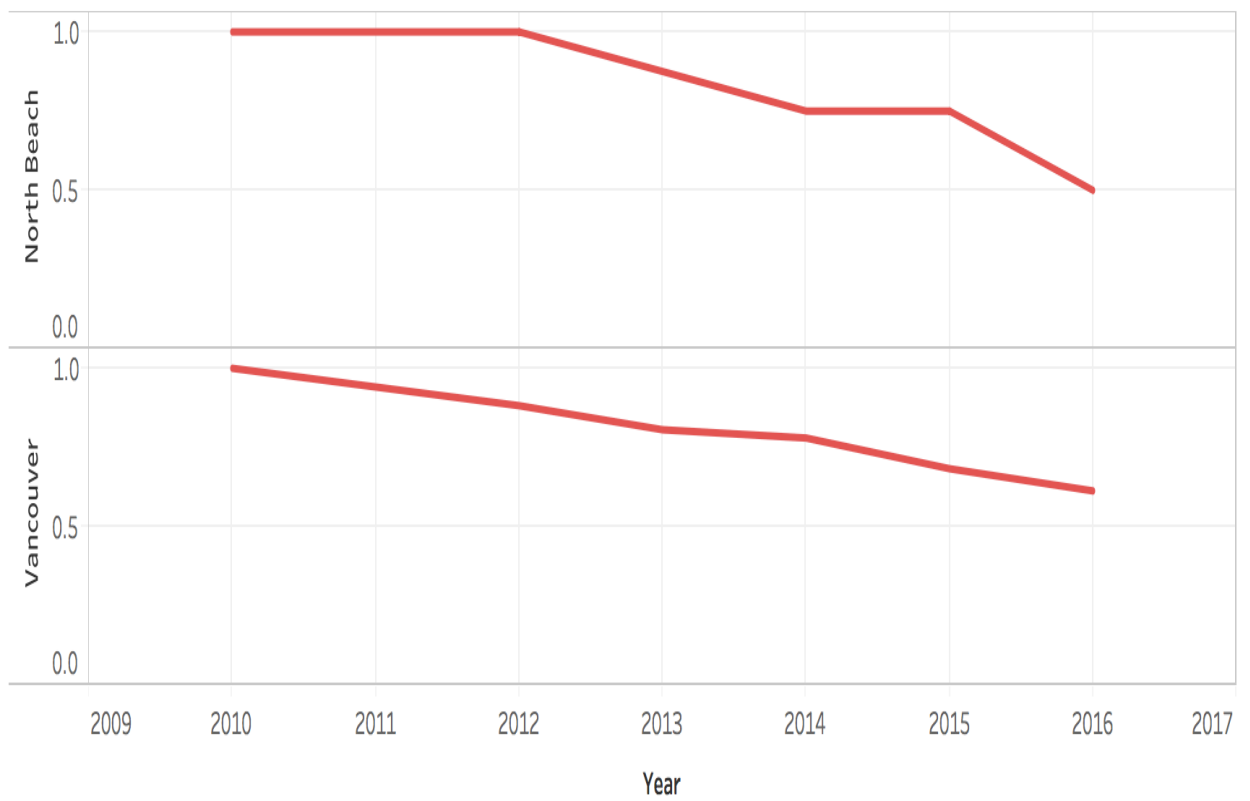
are quite big, containing more than a thousand schools. Some school districts are quite small, containing just several schools. Common sense tells us that urban school districts usually contain more schools than school districts in suburb. I use the simple random sampling method to select a group of 10 school districts to study. The definition of simple random sampling is

“Simple random sampling, or SRS, is often used as a basic design. Simple random samples assign an equal probability of selection to each frame element, equal probability to all pairs of frame elements, equal probability to all triplets of frame elements, and so on” (Survey Methodology, 2<sup>nd</sup> Edition, Groves, et al, 2009).

These ten school districts are generated by the “sample” command in R, which are Touchet School District (22 schools), Paterson School District (10 schools), Centerville School District (4 schools), Bremerton School District (340 schools), Highline School District (1218 schools), Mossyrock School District (37 schools), Grand Coulee Dam School District (43 schools), North Beach School District (51 schools), and Yelm School District (340 schools). The sample of ten school districts is a representative of the whole school district population, each with a certain probability to be chosen. Although my algorithms and

programs can calculate any school district in any year, for convenience we only talk about this sample. Among these ten school districts, Touchet School District, Paterson School District, Centerville School District, Mossyrock School District and Grand Coulee Dam School District are not suitable for calculating the retention rates because the number of schools included within those districts is so small, which would create hard to reach statistical significance. Therefore, I mainly focus on calculating the retention rates for school districts with the number of schools larger than fifty. The retention rates are shown as followed.





Looking at the retention rates on the school district levels, we see that slopes are no longer constant. The school district level retention lines are curved rather than straight as shown by the line of the state level. Two observable things indicated by these two lines are: first, the larger the school district is, the closer the line is to the state level; second, the smaller the school district is, the more unprecedented features captured, for example, the retention rates of Bremerton School District (340 schools) over the year 2012-2013 and 2013-2014 are the same, which means no teacher attritions happened over this two-year period. Same situation happens in the Mossyrock School District (51 schools) over 2010-2012 and 2013-2015. Apparently, one reasonable explanation is that these schools locate in rural area. Teachers in rural area are prone to stay in the same place over time unlike teachers in big cities. The other reasonable explanation is that there was truly no teacher attrition happened over these time periods regardless of the locations.

### **Forecasting Methods for Teachers' Churn Rates**

For statistics, forecasting is usually the most important and hardest part. As you can see, churn rates are not stable among the 11 years. We can use two approaches to forecast the



future movements. One is Machine Learning nonparametric approach, by using Generalized Additive Model (gam) splines smoothing or Locally Weighted Regression (Loess) to smooth the series. The other is Time Series approach, by using the Multiplicative Model  $y_t = T_t * S_t * e_t$  or  $\text{Log}(y_t) = \text{Log}(T_t) + \text{Log}(S_t) + \text{Log}(e_t)$  to forecast. However, the seasonal term and calendar term are not used. It is because the churn rates are yearly based. There has no influence on the churn rates from seasons or length of the month.

A key feature of nonparametric approach is to effectively saturate the predictor space with knots and then protect against overfitting by constraining the impact the knots can have on the fitted values (Berk, R.A. (2016) *Statistical Learning from a Regression Perspective*. Philadelphia, PA: Springer). The algorithm for nonparametric Generalized Additive Model (GAM) is to repeat the following equation until each of the  $p$  predictors has a revised set of fitted values (Berk, R.A. (2016) *Statistical Learning from a Regression Perspective*. Philadelphia, PA: Springer).

$$\hat{f}_j \leftarrow S_j \left[ \{y - \hat{\alpha} - \sum_{k \neq j} \hat{f}_k(x_{ik})\}_1^N \right].$$

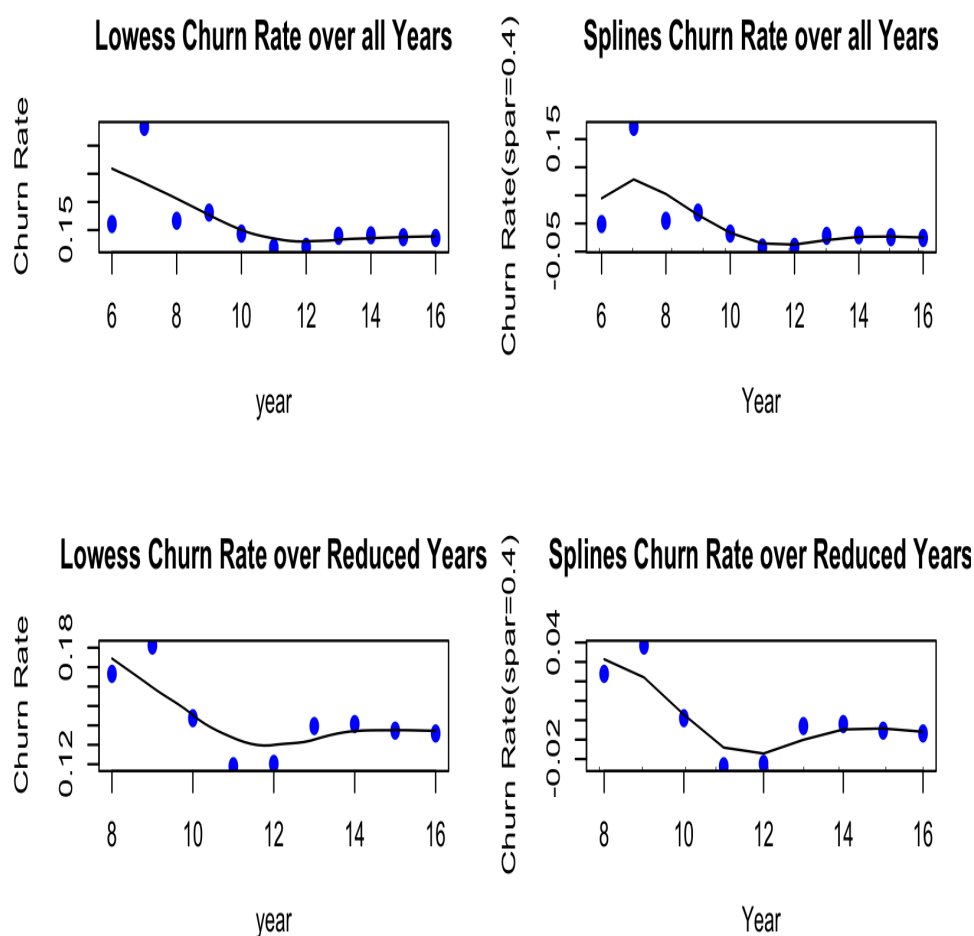
$$\hat{f}_j \leftarrow \hat{f}_j - \frac{1}{N} \sum_{i=1}^N \hat{f}_{ij}$$

We can then specify  $\text{spar}$  to determine the tuning parameter  $\lambda$ . Usually, the smaller the  $\text{spar}$  is, the more graphical the plot will be. The larger the  $\text{spar}$  is, the smoother the plot will be.

Similarly, for Loess regression, it is defined as each local regression at each  $X_0$  is constructed by minimizing the weighted sum of squares with respect to the intercept and slope (Berk, R.A.

(2016) *Statistical Learning from a Regression Perspective*. Philadelphia, PA: Springer).

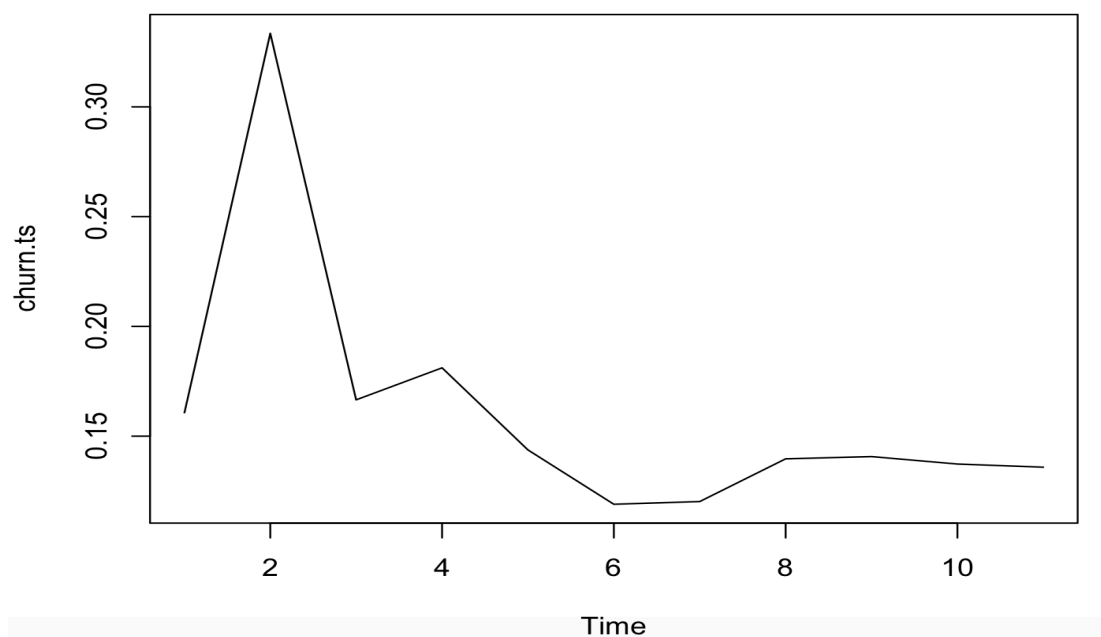
Since there is a significant spike in 2007, I draw four plots. The upper two pictures are the smoothing plots over the 11 years round per each method in smoothing, and the other two are for the reduced years (9 years round except for 2006 & 2007) per each method.



We see that Loess Churn Rate graphs over years are smoother than penalized smoothing splines-GAM graphs. It is because I let computer choose the tuning parameter for the Loess Regression. Normally, computer will choose a tuning parameter with a large number. However, I specify the  $\text{spar}$ , which is the tuning parameter for splines-GAM Curve, to be 0.4. The penalty term is not that big, thus the curve is more graphical. Nevertheless, two graphs simultaneous show that the trend will be stable and slightly decrease in the future, saying, the churn rate in 2017 will be slightly less than the churn rate in 2016.

One more thing I want to notify here is that the package of gam I used is package (“gam”). There are two packages having gam function. The other is “mgcv” package. The reason that I do not use “mgcv” package is because the penalty term in “mgcv” gam function is not bounded to 1, therefore it is harder for me to select the proper value for the tuning parameter.

For the time series approach, I use the time series multiplicative model. The followed is the residual plot of the data.



There are two ways to select the highest power of degrees. One is counting how many bumps or up-down trend in the graph. In our case, there are 4 or 5 up-down trends indicated by the graph. Then, I start fitting the model to the fifth power. Looking at the summary table, we see that the fifth power is not significant. I remove the fifth power term, and remain the fourth power in the regression. Now I see the fourth power is significant, and all the other terms are significant as well. The second way to decide the power is to do a stepwise regression. When we add time variable one by one, we see that the fourth power is significant but the fifth power is not. As required by the stepwise regression, we stop adding variable until two consecutive terms are insignificant. I tried the sixth power, and it is not significant either. It suggests that the model to the power of 4 will be the best one. In addition, since the extreme

value is in the year of 2007, I create a dummy variable to reduce the influence of the extreme value by setting obs07 to be 1 in 2007, and all the other years to be 0. Therefore, we can get the time series forecasting model as follows:

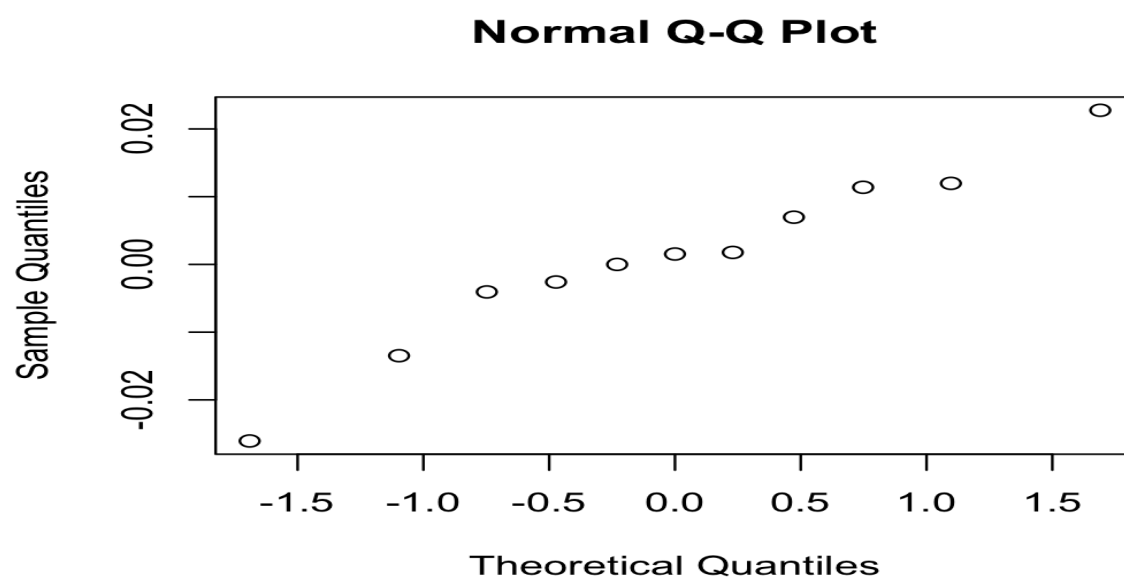
```
Call:
lm(formula = churn ~ 0 + time + I(time^2) + I(time^3) + I(time^4) +
    obs2)

Residuals:
    Min       1Q   Median       3Q      Max
-0.026066 -0.003330  0.001533  0.009178  0.022753

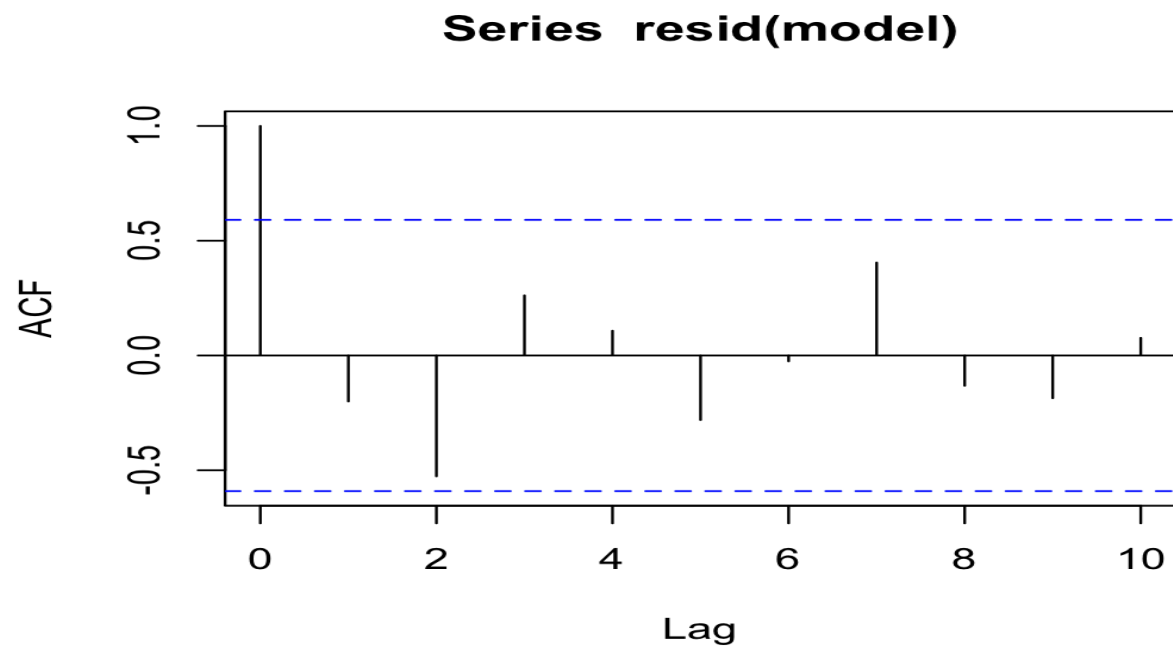
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
time      1.933e-01  1.911e-02  10.117 5.42e-05 ***
I(time^2) -6.243e-02  8.701e-03  -7.175 0.000370 ***
I(time^3)  7.320e-03  1.249e-03   5.863 0.001089 **
I(time^4) -2.859e-04  5.661e-05  -5.051 0.002331 **
obs2      1.425e-01  2.170e-02   6.568 0.000597 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.01697 on 6 degrees of freedom
Multiple R-squared:  0.9947,    Adjusted R-squared:  0.9902
F-statistic: 223.3 on 5 and 6 DF,  p-value: 9.962e-07
```

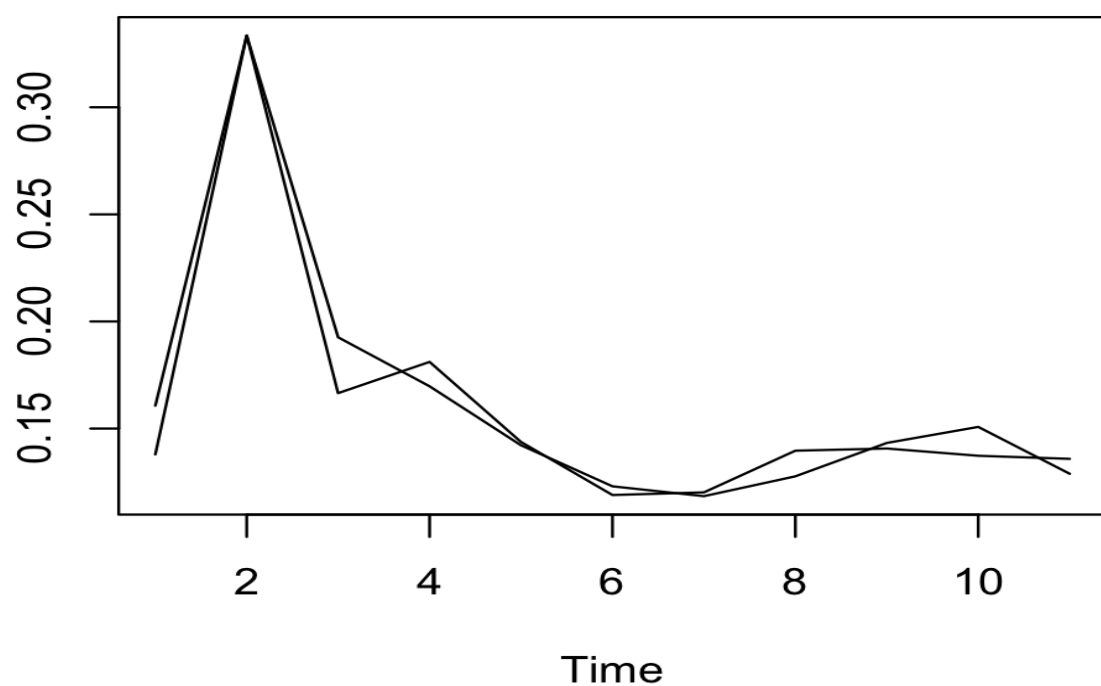
Then we check the fit of the model by looking at the QQPlot, ACF plot.



We see that the qqplot indicates that the normality assumption is satisfied.



The ACF plot shows that the model is reduced to white noise only, which is great. However, the perfectness of the ACF plot may not tell the truth since the number of points is eight, which is too few to reach a meaningful conclusion.



If we put the forecasting graph and the original graph into the same plot, then we see that the forecasting model fits well. The forecasting curve indicates that there should be a drop in the churn rate in the year of 2017 but it will not be too much. We can also calculate the generalization error by using the prediction, which is 0.00017. It is too small. It can tell us two things. One is our time series model fits very well. The other is it might have some inclination of overfitting. However, I cannot improve this much at the time being, because we only have 11 points. The number of points is too small. It is not just possible to create overfitting issues but also may create bias as well.

We may also consider using the Distributed Lag Time Series Model to predict. This model will take consideration into the influence of the previous churn rate may potentially influence the churn rate in the future. To check whether this model is necessary, we can use Durbin-Watson test to see the autocorrelation. However, I think it is not necessary, since churn rate is not like sales. The sales in the year  $t$  may be influenced by the sales in the previous years, or the advertising in the previous years. Nonetheless, we calculated churn rates year by year with different cohorts. It assumes the independence of the churn rate, which is unlike sales or advertising. Therefore, I think the multiplicative model should be

sufficient. However, I may consider using GARCH (1,1) model to fit the regression in the future. GARCH model performs well when the series has instability features. It might be our case, because we see that there is a spike in 2007-2008 due to the recession.

### **Discussion**

Generally speaking, the accuracy of the whole forecasting process largely depends on the calculation of the churn rates. There are many ways to define the churn rates. Therefore, the different definition of the churn rate is, the different forecasting values we will get, even though we stay with the same methods the methods. However, how to get the most unbiased churn rate is tricky because we are lack of official criteria. For this concern, our research panel emailed Washington State for a couple of times, but we still do not get an ascertained answer. For example, the definition of whether a teacher belongs to STEM field is still unclear.

Another thing I want to point out here is about forecasting. In this paper, I introduced two ways of forecasting. One is time series multiplicative model, and the other is the Generalized Additive Model. However, there are so many models have the same functions or



even perform better. For instance, the ARIMA model and Random Forest are two candidates.

ARIMA is widely used in the longitudinal analysis with stationary time series, especially for series with seasonal structures. However, our series has no seasonal structure, and the multiplicative model fits the trend well from regression prospective. Therefore, there is no need for me to develop an ARIMA model to overfit the trend, and which is not necessary. Nevertheless, I will consider applying such a model if in the future we work on the monthly-base data. Random Forest is intensively used for forecasting dichotomous response variables. It is not that useful in our case at this moment. However, it will be extremely useful if we want to concentrate on individual's possibility of changing positions. The advantage of random forest is that it automatically uses bagging procedures to create "OOB" (Out of Bag data), which can be treated as test data to check model accuracy.

What's more, I want to highlight the future goals for this project. First of all, it is a good idea to compare retention rate and churn rate over different levels: state level, district level and school level. It is expected that retention rate and churn rate will be likely higher in school level than district level, and higher in district level than state level. It is because teachers change schools but less likely change place to live. If they live in the same area, but

work in different schools, the retention rate and churn rate will remain the same in district level even some sudden turnovers happen in school levels. Similarly, the retention rate and churn rate in state level will usually maintain the same even there are fluctuations in the district level and school level. Therefore, it explains why the retention rate and churn rate in state level is more stable. Second of all, I am trying to figure out the possible reasons to interpret the movements of churn rates over the years. This can be ascribed to the level III statistics, also known as causal inference. Causal inference in many times serves as a guide for policy makers making future policies. The attrition of teachers impairs the right for students to receive education, and in some ways, is a crucial factor leading to the uneven allocation of resources. As a result, it will aggravate social contradiction that was already existed due to the gap between rich and poor classes. Policy makers can make use of our findings as references to make brighter plans to provide better educations for kids in K-12 program and reduce the gap among resources in different districts or schools. The better education that our kids receive, the brighter future is of our country.

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